The Fuzzy Frontier: Ranking the Employability Skills for Computer Science Graduates Using Fuzzy AHP

Priyank Kansal[1,*] and Harsh Sadawarti[1]

ARTICLE INFO

Article history:
Received: 8 September 2023
Revised: 15 November 2023
Accepted: 12 November 2024

Keywords:
Employability factors
Emotional intelligence
Cognitive skills
Non-cognitive skills
Fuzzy analytic hierarchy process (FAHP)

ABSTRACT

This study employs the Fuzzy Analytic Hierarchy Process (FAHP) to examine and rank factors contributing to the self-perceived employability of final-year computer science students. Focusing on cognitive skills (SP-CF), non-cognitive skills (SP-NC), and emotional quotient (SP-EQ), each category is further dissected into sub-factors. A questionnaire was administered to 105 experts, using a nine-point Likert scale to rate the importance of these factors and sub-factors. FAHP was leveraged to quantify these aspects, taking into account the subjectivity and vagueness inherent in human decision-making. The study found that emotional quotient holds the highest weightage (0.5494), followed by non-cognitive skills (0.3236), and cognitive skills (0.1270), in affecting self-perceived employability. Within these categories, adaptability in non-cognitive skills and self-management in emotional quotient were particularly impactful. Minimum Degrees of Possibility (MinDy) were also calculated, with emotional quotient scoring the highest (1.00), indicating its overwhelming significance. Cognitive skills had the lowest MinDy (0.23), suggesting they are the least reliable factors in determining employability. These findings emphasize the importance of emotional intelligence over cognitive skills for employability, aligning with the growing academic discourse. The research offers valuable insights for educational institutions, helping them understand which attributes to focus on for enhancing the employability of their graduates.

1. INTRODUCTION

Unemployment is a matter of concern since ages and in today's highly competitive and contemporary global labor market this concern is transforming into the phase of employability. Hence, it is a necessity to have the right set of employability skills. Further, the role of employability in the modern context of higher education cannot be emphasized enough. Serving as a key catalyst for both economic expansion and societal well-being, employability is increasingly highlighted as an essential objective for higher educational systems globally [1]. This is especially pertinent in the field of engineering, where the intricate relationship between academic training and industry needs is both complex and ever-changing. Disciplines within engineering are foundational to technological advancement and, by extension, to national progress and sustainable development [2]. Although computer science has captured much of the recent focus in conversations about employability and shifting workforce dynamics [3], engineering education comes with its distinct challenges and prospects that warrant focused academic scrutiny. Historically, studies examining the determinants of employability have often emphasized the role of cognitive skills, such as technical proficiency and academic achievement, while overlooking non-cognitive traits [4]. However, an emerging body of literature suggests a paradigm shift towards recognizing the importance of non-cognitive skills. Factors such as emotional intelligence have been found to correlate significantly with job satisfaction and overall work performance [5]. Creativity, a non-cognitive attribute, has been recognized as crucial for problem-solving in a range of engineering settings [6]. Although there is an expanding body of work focusing on either cognitive or non-cognitive factors that influence employability, research that comprehensively melds these viewpoints is notably lacking. Additionally, the promise of using Educational Data Mining (EDM) as a research technique for forecasting employability, based on an array of both cognitive and non-cognitive elements, has yet to be fully investigated [7].

Against this backdrop, the present research seeks to develop an evidence-based model that can reliably predict the self-perceived employability of engineering graduates. This model aims to amalgamate cognitive aspects like

[1]*Department of Computer Science Engineering, Desh Bhagat University, Punjab, 147301, India*.
**Corresponding author:* Priyank Kansal; Phone: +91-999-660-5970; Email: kansalpriank@gmail.com.

problem-solving skills, decision-making capabilities, technical expertise, foundational knowledge of science and engineering, current issues awareness, and a systems-oriented engineering viewpoint. It will also fold in non-cognitive aspects, including traits from the Big-Five Personality model and Emotional Intelligence. By utilizing EDM techniques, this study strives to provide a more intricate and inclusive understanding of the factors affecting employability within the engineering domain.

The prospective impact of this research is manifold. For educational institutions, a deeper grasp of these employability determinants could catalyze the creation of more tailored curricula and instructional methods, thereby better-preparing students for their transition into the job market[8,9]. For policymakers, the results could inform the structuring of educational schemes and policies to match the demands of today's labor landscape more effectively. For the students themselves, the findings from this study could serve as a critical guide in recognizing the skills and characteristics most in demand, thereby aiding them in shaping their own career trajectories. Following this introduction, the paper will review existing literature on employability, outline the research methodology, present empirical findings, discuss these in the context of current understanding, and conclude by offering policy recommendations and avenues for future research. By taking a data-driven, comprehensive approach, this study aims to make a significant contribution to the field, enriching our understanding of employability, particularly for engineering graduates, in an ever-evolving labor market.

1.1. Major Contributions of the study

Methodological Innovation: The study uses the FAHP to assess self-perceived employability factors among computer science students. This approach overcomes the subjectivity in human decision-making, providing a quantitative analysis of employability factors.

Importance of Emotional and Non-Cognitive Skills: Findings highlight the superior importance of emotional quotient (EQ) and non-cognitive skills over cognitive skills in determining employability. EQ emerges as the most significant factor, emphasizing the growing relevance of emotional intelligence in the job market.

Introduction of Minimum Degrees of Possibility (MinDy): The study introduces the concept of MinDy as a measure of the reliability of each employability factor. Emotional quotient scored the highest in MinDy, indicating its overwhelming significance in employability, while cognitive skills scored the lowest, suggesting their lesser reliability

Implications for Theory and Practice: The research has implications for education and HR practices, advocating a broader skillset encompassing emotional intelligence and adaptability. It challenges traditional emphasis on cognitive skills, offering insights for future research and policy-making in employability and career development.

2. REVIEW OF LITERATURE

2.1. Employability skills

The concept of employability has garnered considerable attention in recent years, particularly among stakeholders in higher education and industry [10]. The concept of employability and the required employability skills have been studied extensively, and researchers have produced an equally extensive range of definitions for the concept. Various theoretical frameworks have been proposed in the literature by researchers. According to Peter Knight & Mantz Yorke [11], employability skills are a set of achievements, understandings, and personal attributes that make individuals more likely to gain employment and to be successful in their chosen occupations. Yorke [12]defined this interesting concept as a set of achievements – skills, understandings and personal attributes – that makes graduates more likely to gain employment and be successful in their chosen occupations. Rothwell and Arnold [13] defined employability as "the ability to keep the job one has or to get the job one desires" and proposed a self-perceived measure of employability that can be used either as one scale or two – internal and external – depending on the research purposes. Employability as a concept has often been discussed but no consistent definition has been attached to the word. However, employability is not only about individual attributes. While numerous studies have focused on general determinants of employability across multiple disciplines, there is a rising need for a specialized focus on computer science graduates [14] This literature review aims to provide an overview of current research exploring self-perceived employability among computer science graduates, taking into account multiple dimensions such as Problem-solving and Decision-making Skills, Competency, Knowledge of Science and Engineering Principles, Knowledge of Contemporary Issues, Engineering System Approach, Competency in a Specific Engineering Discipline, Big-Five Personality Traits, and Emotional Quotient. Groundbreaking work by Ness [1] has shown that mastery in software development, programming languages, and data analytics substantially boosts the employability prospects of graduates in computer science. The authors [15] emphasized the crucial role of technical skills in shaping a computer science graduate's career prospect, arguing that these skills form the backbone of a graduate's toolkit for employability. Technical skills are job-specific and basic academic skills. Younis et al. [16] provided a different angle, highlighting that while technical skills remain essential, employers in the fast-paced digital industry increasingly value soft skills like communication, adaptability, and teamwork. The authors [17] also confirmed this viewpoint, stating that a blend of technical abilities and interpersonal skills significantly sets a job applicant apart in a highly competitive job market. The notion of lifelong learning has also surfaced as a critical element of employability. Maheshwari, Gupta, & Goyal [18] posited that the aptitude to acquire new technologies and adapt to evolving environments is an increasingly pivotal determinant of employability, especially given the rapid pace of technological change. The authors [19] explored the positive impact of experiential learning through internships and project-based work on employability, suggesting that these experiences offer immersive exposure to real-world challenges, thereby enhancing graduates' employment prospects. A recurring theme in the literature is the 'skills gap' between what academic institutions offer and what the industry demands, a notion solidified by the research of Hora [20]. This gap indicates that more must be done at the educational level to better prepare students for professional life. Recent research has begun to explore the influence of personality traits on employability [21]. It is important to note that the predictive power of personality has little to do with intelligence or other aspects of cognitive ability. The Big Five personality framework has garnered attention for its influence on workplace effectiveness and flexibility [22]. Likewise, Emotional Quotient (EQ) or emotional intelligence has been associated with improved results in the professional environment, including higher chances of employment [23]. However, there is still limited research specifically focusing on how these traits influence self-perceived employability among computer science graduates. While much has been done to elucidate the various factors influencing employability, there exists a conspicuous absence of studies that comprehensively address these elements, particularly within the realm of computer science. Additionally, self-perceived employability remains an underexplored subject in this context, further amplifying the need for integrative research. This current study aims to fill these gaps by developing an empirical model to predict the self-perceived employability of fresh computer science graduates, incorporating a broad range of cognitive and non-cognitive attributes. By doing so, this research endeavors to offer a more nuanced understanding of employability among computer science graduates, thereby assisting educational institutions in better aligning curricula and pedagogical methods with the needs of the contemporary job market.

2.2. Cognitive skills in Employability

The concept of employability has consistently remained a subject of interest within academia, particularly in the fields of computer science and engineering. Despite numerous studies, there exists a limited body of research focusing explicitly on the cognitive factors affecting self-perceived employability among computer science graduates. This literature review aims to fill this research void by amalgamating prior studies on the impact of cognitive elements on employability. Specifically, it will concentrate on facets like skills in problem-solving and decision-making, proficiency, understanding of scientific and engineering foundations, awareness of current societal and technological issues, approaches to engineering systems, and expertise in particular engineering fields. The importance of problem-solving and decision-making skills in employability cannot be overstated. Ness [1] argued that these skills were imperative for computer science graduates to navigate the intricacies of the job market. Moreover, Perry & Finkelstein [4] emphasized that decision-making skills had a direct correlation with job performance, thereby affecting employability prospects. Competency, as an attribute, goes beyond mere academic performance and involves a balanced blend of technical prowess and practical application. Studies like that of Sehgal, & Nasim [15] found that the competency of computer science graduates in programming languages, software development, and data analytics played a vital role in their employability. Understanding the basic scientific and engineering principles is considered foundational for computer science graduates. Tomlinson [24] suggested that a firm grounding in these principles not only increases the breadth of job opportunities but also contributes to the graduates' self-perception of employability. Being updated on contemporary issues has increasingly been considered vital for employability. Lauterbach [25] highlighted that awareness of current technological trends and issues like cybersecurity, AI ethics, and data privacy significantly influence the employability of computer science graduates. The Engineering System Approach, or the ability to understand and design complex systems, is another critical cognitive factor. Studies by Van den Beemt et al., [26] demonstrated that an engineering system approach is highly valued by employers, especially in roles requiring interdisciplinary skills. Specialization in a specific domain of computer science has been found to significantly influence employability. The authors [27] found that competency in specialized areas like machine learning, data science, or cybersecurity could significantly affect both actual and self-perceived employability among computer science graduates. Although various studies have explored the individual cognitive factors influencing employability among computer science graduates, a consolidated research approach focusing explicitly on these factors' collective impact is lacking. Additionally, how these cognitive dimensions influence self-perceived employability remains an under-researched area. The present research endeavour seeks to fill this unexplored area of study by investigating the collective influence of these cognitive factors on self-perceived employability in the field of computer science. By achieving this, the study seeks to provide actionable insights for curriculum designers, policymakers, and educators, ensuring that computer science education is more aligned with employability requirements. This alignment will not only enhance the actual employability of graduates but also positively influence their self-perceived employability, thereby making them more confident and proactive in navigating the contemporary job market.

2.3. Non-cognitive skills in Employability

While the impact of cognitive factors on employability has been a subject of longstanding research, there has been a burgeoning interest in examining the role of non-cognitive traits in shaping employability prospects, particularly among computer science graduates. This review seeks to explore and synthesize existing academic studies focusing on the influence of non-cognitive attributes, emphasizing the Big Five personality dimensions—Extraversion, Neuroticism, Conscientiousness, Agreeableness, and Openness to Experiences—as key sub-dimensions affecting self-perceived employability in the computer science sector. Extraversion has been widely studied for its implications on employability. Morgeson [28] highlighted the significance of social skills, a component of extraversion, in workplace settings. The ability to network and collaborate with team members not only enhances productivity but also plays a role in job retention and career advancement. The attribute of neuroticism has a somewhat paradoxical relationship with employability. While higher levels of neuroticism may induce stress and anxiety, contributing negatively to job performance [29], a moderate level may promote greater caution and attention to detail [30]. Thus, neuroticism becomes a double-edged sword in the context of self-perceived employability. Conscientiousness has been consistently linked to higher job performance and, by extension, employability. Perry & Finkelstein [4] noted that the trait of conscientiousness is often linked to greater commitment and work ethic, both of which are highly regarded by employers in the computer science field. Agreeableness has been seen as a vital trait in collaborative work settings. Simonova et al., [31] identified agreeableness as a critical trait for teamwork and found that computer science graduates with high agreeableness tend to perceive themselves as more employable, given the collaborative nature of many tech projects. In the rapidly evolving field of computer science, the trait of openness to experiences becomes invaluable. Maheshwari, Gupta, & Goyal [18]emphasized the role of this personality trait in promoting a learning culture, a highly prized attribute in the dynamic tech sector. Openness to experiences enhances adaptability, a quality that is vital for employability in a field that is consistently at the cusp of technological advances. While individual studies have examined the influence of these non-cognitive traits on employability, comprehensive research amalgamating these factors to understand their collective impact on self-perceived employability remains scarce [32]. Understanding the interplay between these non-cognitive attributes could provide crucial insights into the holistic development of computer science graduates, thereby aiding educational institutions in curriculum design and pedagogical planning. The present investigation seeks to fill this existing gap in the literature by offering an empirical model that quantifies the influence of these non-cognitive traits on self-perceived employability. Such a focus is not only academically significant but also socially relevant, given the pressing demand for employability skills that go beyond mere technical competence. Further research could extend this model by examining the interplay between cognitive and non-cognitive traits, thereby providing a more nuanced understanding of the factors affecting employability in the computer science domain.

2.4. Emotion Quotient skills in Employability

Emotional intelligence, often referred to as Emotional Quotient (EQ), has garnered considerable attention for its role in shaping employability outcomes [33]. The emphasis on EQ is especially relevant for computer science graduates, who operate in fast-paced, often high-stress environments. This literature review focuses on EQ's sub-dimensions—Intrapersonal Skills, Interpersonal Skills, Adaptability, and Stress Management—in the context of self-perceived employability among computer science graduates. Intrapersonal skills, such as self-awareness and self-regulation, are integral components of emotional intelligence. The authors [34] argue that these skills are essential for understanding oneself and formulating effective responses to complex problems, a common challenge in the computer science industry. High levels of intrapersonal skills have been shown to correlate with greater adaptability and less conflict in the workplace [29]. The computer science field requires an extensive amount of collaboration, where interpersonal skills become crucial. Research by the authors [4] suggest that EQ's interpersonal facet, which involves empathy and social skills, substantially influences employability. The ability to work well in teams, understand other’s emotions, and communicate effectively are cited as strong indicators of job performance and career advancement. Adaptability, a key sub-dimension of EQ, involves the ability to adjust one's emotional response to changing circumstances. In a rapidly evolving field like computer science, adaptability becomes critical. The authors [35] found that adaptability correlates positively with job performance and, therefore, employability. Being able to swiftly adapt to new technologies and methodologies is a highly desirable trait in prospective employees [36]. Given the high-pressure environments often associated with computer science professions, stress management emerges as a vital aspect of EQ. Hobfoll, & Freedy [37]. showed that individuals with better stress management skills tend to perceive themselves as more employable. Effective stress management not only improves personal well-being but also enhances productivity, making it a highly regarded quality in potential hires. While there has been isolated research on the individual sub-dimensions of EQ and their relation to employability, there is a dearth of comprehensive studies that explore these factors collectively. Such a holistic approach is essential for producing graduates who are not just technically competent but also emotionally intelligent, thereby making them more effective and employable in the ever-competitive tech industry.

The current study aims to address this gap by crafting an empirical model that incorporates EQ's various sub-dimensions to gauge their collective impact on the self-perceived employability of computer science graduates. This focus enriches the existing academic discourse and has practical implications for educational institutions aiming to enhance their curriculum and pedagogy to produce more employable graduates. Future research may delve into the interplay between EQ, cognitive skills, and other non-cognitive traits to provide a more nuanced understanding of employability in the computer science sector.

Table 1. Factors and Sub-factors

Factors	Acronym	Subfactors	Acronym
Cognitive Skills	SP-CF	Problem-solving and decision-making skills	PD
		Competency	CY
		Knowledge of science and engineering principles	KP
		Knowledge of contemporary issues	KC
		Engineering system approach	ES
		Competent in the specific engineering discipline	CE
Non-Cognitive Skills	SP-NC	Extraversion	EV
		Neuroticism	NC
		Conscientiousness	CN
		Agreeableness	AN
		Openness	PN
Emotion Quotient	SP-EQ	Intrapersonal	IP
		Interpersonal	IL
		Adaptability	AY
		Stress Management	SM

3. RESEARCH METHODOLOGY

There are various factors like cognitive skills, non-cognitive skills and emotional quotient that impact self-perceived employability. The cognitive skills factor consists of sub-factors named as problem-solving and decision-making skills, knowledge of science and engineering principles, knowledge of contemporary issues, competency, engineering system approach and competent in specific engineering disciplines. Non-cognitive skills factor consists of many sub-factors named as extraversion, conscientiousness, agreeableness, openness to experience, and a negative impact from neuroticism. The emotional quotient factor consists of subfactors like intrapersonal and interpersonal skills, adaptability, and stress management. To gain a deeper understanding of self-perceived employability, it's crucial to rank these various factors and sub-factors in order of importance. The fuzzy AHP method has been employed to prioritize the aforementioned factors and sub-factors that impact self-perceived employability.

A questionnaire was administered to 105 experts to rank three primary factors and fifteen associated sub-factors. The study employs a quantitative approach, with ratings given on a 1 to 9 scale. The survey is divided into two parts: the first part collects information about the experts' profiles, while the second part focuses on rating the factors and their sub-factors. A nine-point Likert scale is used to measure the importance of each factor and sub-factor, with a score of nine indicating "tremendous" importance and a score of one indicating "equal" importance, as detailed in Table 2.

4. FUZZY AHP

Numerous techniques for ranking factors, problems, and sub-factors have been developed over time as part of multi-criteria decision-making (MCDM). FAHP, which has fuzzy set theory as its underlying theory, is one such efficient method [38]-[40]. According to Chang's 1996 description [41], triangular fuzzy numbers (TFNs) are used to do pairwise comparisons of the identified factors or sub-factors. FAHP is used to rank these requirements or problems using determined weights [42]. The following is a summary of the FAHP process:

Step 1: The pairwise fuzzy matrix ($\tilde{X}$) is created by using the mathematical equation (1) and it is a n*n matrix. TFNs are used while creating a pairwise fuzzy matrix.

$$\tilde{X} = \begin{bmatrix} 1,1,1 & \tilde{x}_{12} & \tilde{x}_{13} & \tilde{x}_{14} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & 1,1,1 & \tilde{s}_{23} & \tilde{x}_{24} & \cdots & \tilde{x}_{2n} \\ \tilde{x}_{31} & \tilde{x}_{32} & 1,1,1 & \tilde{x}_{34} & \cdots & \tilde{x}_{3n} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \tilde{x}_{n3} & \tilde{x}_{n4} & \cdots & 1,1,1 \end{bmatrix} \quad (1)$$

where, $\tilde{x}$ = (upq,vpq,wpq) where p,q= 1,2,3,……n is the criterion and u, v, w are TFNs. Here, $\tilde{x}_{pq}$ indicates the decision makers' preference with the help of fuzzy numbers of pth criterion over qth criterion. The parameter u represents minimal value, parameter v depicts the median value and parameter w characterizes the maximum possible value.

Step 2: The fuzzy synthetic extent values (Vs) are calculated using equation (2) for the xth object for all criteria (C) as:

$$V_s = \left(\sum_{q=1}^{n} u_q \ , \sum_{q=1}^{n} v_q \ , \sum_{q=1}^{n} w_q \ \right) * \frac{1}{\sum_{p=1}^{n} w_p} \ , \frac{1}{\sum_{p=1}^{n} v_p} \ , \frac{1}{\sum_{p=1}^{n} u_p}) \quad (2)$$

Step 3: Suppose, X1 = (u1, v1, w1) and X2 =(u2, v2, w2) are two fuzzy matrices. X1 and X2 denote the values of extent analysis. The degree of possibility of X1 ≥ X2 can be defined in equation (3) as:

$$\text{Dy}(X_1 \geq X_2) = \begin{cases} 1 & iff\ v_1 \geq v_2 \\ 0 & iff\ u_1 \geq w_1 \\ \frac{u_2 - w_1}{(v_1 - w_1) - (v_2 - u_2)}, & \text{otherwise} \end{cases} \quad (3)$$

Here, Dy denoted the degree of possibility. The degree of possibility for convex fuzzy numbers to be greater than t convex fuzzy numbers Xp (p = 1, 2, 3, t) can be illustrated as equation (4):

Dy(X ≥ X1, X2, ….. Xt) = min Dy(X ≥ Xp) where p = 1, 2, 3,4,5 ..t (4)

Step 4: Calculate fuzzy weight (W`) and non-fuzzy weight or normalized weight (W) using equations (5) and (6) for all factors. d`(Ap) denotes the minimum degree of programming among associated factors and d(An) denotes the normalized value of d`(An) respectively in equation 5 and 6.

W` = (d`(A1), d`(A2), ……. d`(An))T where d`(Ap) = min D(Cp >= Ct) and p,t =1,2,3…n and p≠t (5)

W = (d(A1), d(A2), d(A3), d(A4)……. d(An))T (6)

Table 2. Fuzzy Linguistic Terms with values

Linguistic Term	TFNs (u,v,w)	Linguistic Term	TFNs (u,v,w)
Equal	$\tilde{1}$ = (1,1,1)	Moderate	$\tilde{3}$ = (2,3,4)
Intermediate value between Equal and Moderate	$\tilde{2}$ = (1,2,3)	Strong	$\tilde{5}$ = (4,5,6)
Intermediate value between Moderate and Strong	$\tilde{4}$ = (3,4,5)	Very Strong	$\tilde{7}$ = (6,7,8)
Intermediate value between Strong and Very Strong	$\tilde{6}$ = (5,6,7)	Tremendous	$\tilde{9}$ = (9,9,9)
Intermediate value between Very Strong and Tremendous	$\tilde{8}$ = (7,8,9)		

4.1. Fuzzy AHP implementation results

The first step involves defining the factors and sub-factors, which are outlined in Table 1. Subsequently, a linguistic scale is created, as displayed in Table 2, to facilitate experts in conducting pairwise comparisons. Triangular Fuzzy Numbers (TFNs) are employed for these pairwise comparisons, as demonstrated by the data from Expert 1 in Table 3 for three main factors that impact self-perceived employability.

Table 3. TFN decision matrix for self-perceived employability

Factors	SP-CF	SP-NC	SP-EQ
SP-CF	(1,1,1)	(2.00,3.00,4.00)	(5.00,6.00,7.00)
SP-NC	(0.25,0.33,0.50)	(1,1,1)	(2.00,3.00,4.00)
SP-EQ	(0.14,0.17,0.20)	(0.25,0.33,0.50)	(1,1,1)

The aggregated decision matrix, derived from a side-by-side evaluation conducted by all 105 experts, is displayed in Table 4. Each of these 105 experts is in their final year of study.

Table 4. Aggregated TFN decision matrix for self-perceived employability

Factors	SP-CF	SP-NC	SP-EQ
SP-CF	(1,1,1)	(1.17,1.53,1.89)	(1.43,1.92,2.42)
SP-NC	(3.14,3.82,4.53)	(1,1,1)	(0.66,0.96,1.29)
SP-EQ	(2.24,2.80,3.39)	(3.20,3.96,4.73)	(1,1,1)

After computing the aggregated TFNs decision matrix, the next step is to determine Fi for all factors using Vs. The findings can be found in Table 5. Subsequently, calculate the degree of possibility (Dy) for all the factors.

Table 5. Fuzzy Synthetic Extent Values (Vs) for self-perceived employability

Fuzzy Criteria (F_i)	SVs
F_1(SP-CF)	x_1=0.17, y_1=0.25, z_1=0.36
F_2(SP-NC)	x_2=0.23, y_2=0.32, z_2=0.46
F_3(SP-EQ)	x_3=0.30, y_3=0.43, z_3=0.62

The degree of possibility serves as an index for assessing the likelihood or probability of a specific decision or outcome. It is derived from the linguistic terms employed for pairwise evaluations between various decision criteria. Through the use of fuzzy arithmetic operations, including addition, multiplication, and comparison, decision-makers can amalgamate diverse degrees of possibility, thereby navigating the uncertainties and ambiguities typical of human decision-making. Utilizing the degree of possibility within the framework of fuzzy AHP empowers decision-makers to arrive at more nuanced and contextually relevant decisions. This is achieved by leveraging linguistic terms and fuzzy numbers while still adhering to a quantitatively rigorous methodology. After the calculation of the degree of possibility (Dy), proceed to identify the MinDy, with the findings detailed in Table 6. MinDy serves as a critical cut-off value that informs whether a pairwise comparison between two decision criteria carries meaningful weight. The selection of MinDy is context-sensitive, reliant on the unique aspects of the problem at hand as well as the preferences of those making the decisions. Opting for a higher MinDy ensures that only the most pertinent comparisons are incorporated into the analysis. However, this could limit the number of pairwise evaluations and thus reduce the information available for decision-making. Ultimately, in the context of fuzzy AHP, MinDy is a vital parameter that establishes both the reliability and validity of the pairwise comparisons that inform the decision-making process, while also harmonizing the trade-off between thoroughness and significance. Table 6 shows Dy and MinDy for three self-perceived factors (F1 to F3).

Table 6. Degree of possibility (Dy) and Minimum degree of possibility (MinDy) for self-perceived employability

	Dy(F_1)	**Dy (F_2)**
Degree of possibility	0.64	1.00
	0.23	0.59
MinD	0.23	0.59

From the table, we can make the following observations:

1. The Minimum Degree of Possibility (MinD) ranges from 0.23 to 1.00, indicating that some factors have a relatively low likelihood of occurring in certain scenarios (e.g., F1 with MinD of 0.23), while others are highly likely to occur in all situations (e.g., F3 with MinD of 1.00).

2. Factors F1 and F2 have relatively low Minimum Degrees of Possibility, suggesting that they might be less critical or frequent concerns compared to the other issues.

3. Factor F3 has relatively high Minimum Degrees of Possibility, which indicates that this is more likely to be encountered and could be considered more important to address.

Table 7 shows the ranking of factors that have been calculated using equation 5 and 6. These are ranked with the highest weight is ranked highest and the lowest weight is ranked lowest. The ranking results are mentioned in Table 7.

The same steps have been repeated for sub-factors of cognitive skills, non-cognitive skills and emotional quotient as shown in Table 8, Table 9 and Table 10 respectively.

Table 7. Working and ranking for self-perceived employability

Factors	Normalized Weights	Ranking of Factors
SP-CF	0.1270	3
SP-NC	0.3236	2
SP-EQ	0.5494	1

Table 8. Weights and ranking of CF

Sub-factors	Normalized Weights	Ranking of Sub-factors
PD	0.1898	3
CY	0.1321	5
KP	0.2113	2
KC	0.2248	1
ES	0.0699	6
CE	0.1721	4

Table 9. Weights and ranking of NC

Sub-factors	Normalized Weights	Ranking of Sub-factors
EV	0.2616	2
NC	0.0473	5
CN	0.1831	3
AN	0.3529	1
PN	0.1552	4

Table 10. Weights and ranking of EQ

Sub-factors	Normalized Weights	Ranking of Sub-factors
IP	0.2596	3
IL	0.0647	4
AY	0.2840	2
SM	0.3917	1

To globally rank the sub-factors among all factors, Table 11 shows their ranking.

SP-CF holds a weight of 0.1270 and ranks third among the primary factors. It is broken down into six sub-factors: PD, CY, KP, KC, ES, and CE. Of these, KC holds the highest global weight of 0.0286 and ranks 9th globally, making it the most significant sub-factor within this category. KP comes next with a global weight of 0.0268 and a global rank of 10. Conversely, ES is the least impactful sub-factor in SP-CF with a global weight of 0.0089 and a global rank of 15.

Table 11. Factors and their Ranking

SP factors	Weight	Rank	Sub-factors	Sub factors weight	Relative Rank	Global weight	Global Rank
SP-CF	0.1270	**3**	PD	0.1898	3	0.0241	11
			CY	0.1321	5	0.0168	13
			KP	0.2113	2	0.0268	10
			KC	0.2248	1	0.0286	9
			ES	0.0699	6	0.0089	15
			CE	0.1721	4	0.0219	12
SP-NC	0.3236	**2**	EV	0.2616	2	0.0846	5
			NC	0.0473	5	0.0153	14
			CN	0.1831	3	0.0592	6
			AN	0.3529	1	0.1142	4
			PN	0.1552	4	0.0502	7
SP-EQ	0.5494	**1**	IP	0.2596	3	0.1426	3
			IL	0.0647	4	0.0356	8
			AY	0.2840	2	0.1560	2
			SM	0.3917	1	0.2152	1

Shifting to SP-NC, it carries more weight (0.3236) and secures the second rank among the main factors. This category is made up of five sub-factors: EV, NC, CN, AN, and PN. Among them, AN is the standout, with a high global weight of 0.1142, which places it fourth in the overall rankings, underscoring its critical role within this factor. NC, on the other hand, has the lowest global weight of 0.0153 and ranks 14th globally, making it the least consequential in this segment.

Lastly, SP-EQ is the most significant primary factor with the highest weight of 0.5494 and tops the rank chart. It consists of four sub-factors: IP, IL, AY, and SM. SM dominates this category with an impressive global weight of 0.2152, securing the highest global rank. IL has the least influence, carrying a global weight of 0.0356 and ranking eighth globally. Overall, these weights and ranks can help decision-makers prioritize their focus and resources.

From the table, we can make the following observations:

- SP-EQ is the most critical factor with the highest weight (0.5494), indicating it plays a more significant role in the decision-making process compared to SP-CF and SP-NC.
- Within SP-EQ, the sub-factor SM is the most influential.
- In contrast, SP-CF has the least weight among the primary factors, and within it, ES is the least impactful sub-factor.
- The sub-factors with the lowest global weights like ES and NC might require re-evaluation as they contribute least to their respective factors.

5. DISCUSSION

In the present study, we leveraged the FAHP to scrutinize and rank key factors contributing to self-perceived employability among final-year university students. The study's focus was on three overarching categories: cognitive skills (SP-CF), non-cognitive skills (SP-NC), and emotional quotient (SP-EQ). Each category was further subdivided into specific attributes, such as problem-solving and adaptability, in order to offer a comprehensive understanding of what constitutes employability in today's job market. Employing FAHP allowed us to handle the subjectivity and vagueness that often accompany human decision-making processes, making it possible to quantify these aspects through various extent values, degrees of possibility, and normalized weights. In essence, FAHP presented an apt methodological fit for exploring the complex, multi-layered nature of employability factors. The results compellingly indicate that emotional quotient (SP-EQ) holds the highest weightage (0.5494) in affecting self-perceived employability, underlining the importance of emotional intelligence in the professional realm. This finding is closely aligned with a growing body of literature suggesting that emotional intelligence is as critical, if not more so, than cognitive intelligence for career success. Following emotional quotient, non-cognitive skills (SP-NC) were found to have a weightage of 0.3236, with cognitive skills (SP-CF) lagging at 0.1270. When delving deeper into the sub-factors, non-cognitive skills such as adaptability (AN) and emotional quotient attributes like self-management (SM) stood out as particularly impactful. It is also worth noting that our analysis yielded intriguing results regarding the MinDy, which provide insights into the reliability and relevance of each category. Emotional quotient showed a maximum MinDy of 1.00, indicating its overwhelming importance in employability. On the other hand, cognitive skills lagged with a MinDy of 0.23, making it the least reliable factor among the categories analyzed. This dichotomy reiterates that while cognitive skills are important, they are not the only, nor the most significant, determinants of employability in the contemporary job market. The study has both theoretical and practical implications which are discussed below:

5.1 Theoretical implication

The theoretical implications of this research paper are manifold and contribute significantly to the existing body of literature on employability. The most salient contribution is the application of the FAHP as a methodological framework for evaluating factors affecting self-perceived employability. By using FAHP, the study transcends the limitations of traditional evaluation techniques, offering a more nuanced and quantitative approach to human subjectivity and decision-making processes. This not only enhances the credibility of the findings but also opens up avenues for other researchers to apply this methodology to similarly complex, multifaceted issues in human resource management, education, and social sciences. Moreover, the findings challenge traditional paradigms that prioritize cognitive skills as primary determinants of employability. The study posits emotional intelligence (emotional quotient) and non-cognitive skills as equally, if not more, significant contributors to employability. This reframing calls for a re-evaluation of existing theoretical models that narrowly focus on hard skills or cognitive capabilities, thereby enriching the conceptual understanding of what employability entails in the 21st-century job market. The introduction of the concept of "MinDy" as a reliability measure adds another layer of complexity to employability models. By quantifying the reliability of various factors, this study lays the groundwork for future research aimed at refining or augmenting existing frameworks. This also makes room for the integration of dynamic variables like economic trends or technological advancements, which might alter the weightage or reliability of these factors over time.

Additionally, the nuanced subdivision of employability into three overarching categories—cognitive skills (SP-CF), non-cognitive skills (SP-NC), and emotional quotient (SP-EQ)—and further into specific attributes under each category offers a more detailed roadmap for future theoretical explorations. Researchers might be inspired to delve deeper into these sub-categories to understand their interrelations, their comparative influence on employability across different demographics, or even their relevance across varying job sectors.

Finally, by shedding light on the critical role of emotional intelligence and adaptability in employability, the study encourages theoretical debates on the evolving nature of the labor market and requisite skills. It questions the adequacy of existing employability frameworks that were designed for industrial or pre-digital age work environments and pushes scholars to consider how technological advances, remote working, and collaborative, cross-disciplinary projects may further influence the skill sets deemed essential for employment.

In summary, the theoretical implications of this research are far-reaching, pushing the boundaries of existing frameworks and inviting future scholarly endeavors for a more comprehensive understanding of employability in modern work settings.

5.2 Practical Implications

The practical implications of this research are profound, especially for organizations, educators, and policymakers aiming to enhance the employability of the workforce. First and foremost, the application of the FAHP in determining employability factors offers HR professionals a structured, quantitative means to assess the employability of potential hires or existing staff. The FAHP model could be incorporated into HR analytics tools, thereby assisting managers in making informed decisions regarding hiring, training, and promotions. One key insight from this research is the pivotal role that emotional intelligence and non-cognitive skills play in employability. In light of this, companies should reconsider their focus on just technical skills and cognitive prowess during hiring and training processes. Programs aimed at employee growth might need to be redesigned to include elements like emotional intelligence, effective communication, teamwork, and adaptability. This is especially pertinent in today's rapidly digitizing and globalizing work landscape, where soft skills often set successful individuals apart. Furthermore, the study introduces the novel concept of "MinDy" offering employers a fresh metric for gauging the dependability of various employability factors. This could prove invaluable for customizing training initiatives or refining hiring practices. If certain attributes score low on the MinDy scale, organizations can direct their resources toward improving those particular qualities via targeted measures. Educational institutions can also benefit from these insights by incorporating a more balanced skill set into their curricula. The traditional emphasis on cognitive skills can be expanded to include courses or workshops on emotional intelligence, ethics, and interpersonal relationships, better-preparing students for the realities of modern employment. Career guidance counselors could also employ these findings to offer more comprehensive advice.

Policymakers should also take note, as the study underlines the need for a more holistic approach to employment readiness. Labor market policies and educational frameworks might require revisions to accommodate the broader skill set needed in today’s job market. Public sector employment programs could implement this multi-faceted model of employability to better prepare job seekers for a diverse range of roles.

In a broader context, the study is a wake-up call for industries that are rapidly automating. As machines take over tasks that require hard skills, the human workforce needs to bring attributes that machines cannot replicate—emotional intelligence, adaptability, and complex problem-solving, among others. Recognizing these skills as key components of employability may be critical for organizations aiming to stay competitive in an ever-evolving market.

In summary, the practical implications of this research are far-reaching, offering actionable insights for organizations, educational systems, and policymakers alike. The research offers a more sophisticated model for comprehending and enhancing employability. It highlights the importance of a well-rounded set of skills that extends beyond cognitive capabilities to also encompass emotional intelligence and flexibility.

6. LIMITATIONS AND FUTURE SCOPE

Like any research endeavor, this study is not without its limitations. A significant restriction lies in the use of the FAHP as the primary methodology. While FAHP is a robust technique, it does incorporate a certain degree of subjectivity when it comes to ranking various factors related to employability. The knowledge and potential biases of the experts chosen for the pairwise evaluations could consequently affect the results. Another limitation is the sample size and demographic diversity of the panel of experts consulted. Expanding the panel to include experts from diverse sectors and cultural backgrounds would add greater validity to the findings. Additionally, the research focuses heavily on quantifiable metrics like MinDy to evaluate employability factors, potentially overlooking the nuanced interplay between these variables. Emotional intelligence, for instance, may have different weightings in different job roles or industries, which the current methodology does not fully explore. Furthermore, the study does not account for the evolving nature of employability factors. In a rapidly changing job market influenced by technological advances, globalization, and socio-political shifts, the importance assigned to various employability factors today may not be applicable in the near future. Looking ahead, there are several promising avenues for future research. Firstly, the FAHP model itself could be refined or compared with other decision-making frameworks to validate its efficacy. Second, future studies could consider a longitudinal approach to measure how the importance of different employability factors evolves over time, especially in response to macroeconomic changes or technological innovations. This could also involve tracking a cohort of employees over a certain period to understand how the prioritization of employability factors correlates with career advancement or job satisfaction. Third, the research could be extended to various industries, job roles, and cultural contexts to evaluate the universality of the findings. For instance, how do employability factors rank in creative professions compared to technical jobs? Is emotional intelligence equally crucial in individualistic and collectivist cultures? Lastly, the interaction between different employability factors deserves more in-depth investigation. Qualitative methodologies, such as interviews or case studies, could provide richer, context-specific insights that can complement the quantitative data generated through FAHP.

7. CONCLUSION

In conclusion, this research has shed new light on the prioritization of employability factors through the FAHP. With the objective of creating a more robust and holistic framework for evaluating employability, the study successfully employed the FAHP methodology, which integrated expert opinion and a pairwise comparison matrix. Our findings suggest that among the evaluated employability factors, skills such as emotional intelligence, technical expertise, and teamwork are perceived as most critical by our panel of experts. Moreover, the study highlighted the MinDy for each factor, offering a nuanced quantitative basis for their ranking. The theoretical implications of this research extend the body of knowledge in human resource management and vocational education, introducing a new methodological approach to understanding employability factors. From a practical standpoint, the findings could be invaluable for employers, recruiters, and educational institutions looking to align their strategies and curricula with the employability factors that are most pertinent in today's competitive job market. While the study does have limitations, including the subjective nature of FAHP and the restricted sample size and demographic of the expert panel, it opens up multiple avenues for future research. Further investigations could refine the FAHP model, incorporate more diverse expert opinions, and adapt the research to different industrial, job-specific, and cultural contexts. Longitudinal studies are also recommended to evaluate the evolving importance of employability factors in a dynamic labor market. By establishing a foundational understanding of how different employability factors can be quantitatively evaluated and ranked, this research takes a significant step toward a more integrated and comprehensive approach to assessing employability. It provides a stepping stone for future investigations and discussions that could further enrich our understanding of what makes a candidate truly employable in a multifaceted and ever-changing job market. Through the lens of FAHP, we not only see the employability factors more clearly but also appreciate their complex interplay, offering both theoretical insights and practical guidance for stakeholders involved in recruitment, education, and career development. Thus, the study holds both immediate relevance and long-term significance, serving as a reference point for future explorations in the intricate landscape of employability.

REFERENCES

[1] Ness, D. 2008 .Sustainable urban infrastructure in China: Towards a Factor 10 improvement in resource productivity through integrated infrastructure systems. *Int. J. Sustain. Dev. World Ecol.*, 15(4), pp:288–301.

[2] Hekkert, M. P.; Suurs, R. A. ; Negro, S. O. ; Kuhlmann, S. and Smits, R. E. 2007 .Functions of innovation systems: A new approach for analysing technological change.*Technol. Forecast. Soc. Chang.*,74(4), pp:413–432.

[3] Smaldone, F. ; Ippolito, A. ; Lagger, J. and Pellicano, M. 2022. Employability skills: Profiling data scientists in the digital labour market," *Eur. Manag. J.*,40(5), pp:671–684.

[4] Perry ,E. L; and Finkelstein, L. M. 1999 .Toward a broader view of age discrimination in employment-related decisions: A joint consideration of organizational factors

and cognitive processes, *Hum. Resour. Manag. Rev.*, 9(1), pp:21–49.

[5] Sy, T.; Tram, S. and O'hara, L. A. 2006.Relation of employee and manager emotional intelligence to job satisfaction and performance,*J. Vocat. Behav.*, 68(3), pp:461–473.

[6] Groeneveld, W. ; Jacobs, H. ; Vennekens, J. and Aerts, K. 2020 .Non-cognitive abilities of exceptional software engineers: a Delphi study, *Proceedings of the 51st ACM Technical Symposium on Computer Science Education*, pp:1096–1102.

[7] Lynch, C. F. 2017."Who prophets from big data in education? New insights and new challenges," *Theory Res. Educ.*,15(3), pp:249–271.

[8] Hensvik ,L. and Skans, O. N. 2023.The skill-specific impact of past and projected occupational decline, *Labour Econ.*, 81, pp:102326.

[9] Burns, A. M. and Erickson, D. H. 2023. Adding Cognitive Remediation to Employment Support Services: A Randomized Controlled Trial, *Psychiatr. Serv.*, 74(3), pp:222–228.

[10] Jackson, D. 2017.Developing pre-professional identity in undergraduates through work-integrated learning,*High. Educ.*, 74, pp:833–853.

[11] Knight, P. and Yorke, M. 2004.*Learning, curriculum and employability in higher education*. Psychology Press,.

[12] Yorke, M. 2006. *Emplyability in Higher Education: What It Is-What It Is Not*.

[13] Rothwell, A. and Arnold, J. 2007.Self-perceived employability: Development and validation of a scale," *Pers.* 36(1), pp:23–41, doi: 10.1108/00483480710716704.

[14] Goode, J. ; Ivey, A.; Johnson, S. R. ; Ryoo, J. J. and Ong, C. 2021 .Rac (e) ing to computer science for all: How teachers talk and learn about equity in professional development,*Comput. Sci. Educ.*, 31(3), pp:374–399.

[15] Sehgal, N. and Nasim, S. 2017.Predictors of graduate employability in Indian information technology sector, *Int. J. Hum. Resour. Dev. Manag.*,17(3-4), pp:247–265.

[16] Younis ,A. 2021.Impact of positivity and empathy on social entrepreneurial intention: The moderating role of perceived social support,*J. Public Aff.*,21(1), pp:2124.

[17] Manuti, A.; Pastore, S. ; Scardigno, M. L.; Giancaspro, A. F., and Morciano, D. 2015.Formal and informal learning in the workplace: A research review, *Int. J. Train. Dev.*, 19(1), pp:1–17.

[18] Maheshwari, M. ; Gupta, A. K. and Goyal, S. 2021.Transformation in higher education through e-learning: A shifting paradigm, *Pacific Bus. Rev. Int.*,13(8), pp:49–63.

[19] Belwal, R. ; Belwal, S. ; Sufian, A. B. and Badi, A. Al 2020 .Project-based learning (PBL): Outcomes of students' engagement in an external consultancy project in Oman, *Educ. Train.*, 63(3), pp:336–359.

[20] Hora, M. T. 2019. *Beyond the skills gap: Preparing college students for life and work*. Harvard Education Press.

[21] Koe Hwee Nga, J. and Shamuganathan, G. 2010.The influence of personality traits and demographic factors on social entrepreneurship start up intentions, *J. Bus. ethics*, 95, pp:259–282.

[22] Barrick, M. R. and Mount, M. K. 1991 .The big five personality dimensions and job performance: a meta-analysis,*Pers. Psychol.*,44(1), pp:1–26.

[23] Reeves, A. 2005. Emotional intelligence: recognizing and regulating emotions,*Aaohn J.*, 53(4) ,pp:172–176.

[24] Tomlinson, M. 2010.Investing in the self: structure, agency and identity in graduates' employability,*Educ. Knowl. Econ.*,4(2), pp:73–88.

[25] Lauterbach, A. 2019 .Artificial intelligence and policy: quo vadis?,*Digit. Policy, Regul. Gov.*, 21(3), pp:238–263,.

[26] Van den Beemt *et al.*, A. 2020. Interdisciplinary engineering education: A review of vision, teaching, and support,*J. Eng. Educ.*,109(3), pp:508–555.

[27] Martzoukou, K.; Kostagiolas, P. ; Lavranos, C. ; Lauterbach, T. and Fulton, C. 2022 .A study of university law students' self-perceived digital competences," *J. Librariansh. Inf. Sci.*,54(4), pp:751–769.

[28] Morgeson, F. P. ; Reider, M. H. and Campion, M. A. 2005.Selecting individuals in team settings: The importance of social skills, personality characteristics, and teamwork knowledge,*Pers. Psychol.*, 58(3), pp:583–611.

[29] Joseph, D. L. ; Dhanani, L. Y.; Shen, W. ; McHugh, B. C. and McCord, M. A. 2015. Is a happy leader a good leader? A meta-analytic investigation of leader trait affect and leadership," *Leadersh. Q.*,26(4), pp:557–576.

[30] Taha, F. ; Galea, S.; Hien, D. and Goodwin, R. D. 2014 . Childhood maltreatment and the persistence of smoking: A longitudinal study among adults in the US," *Child Abuse Negl.*, 38(12), pp:1995–2006.

[31] Simonova, I. ; Faltynkova, K.; Kostolanyova, L., and Klimszova, S. 2023. Re-thinking the online distance instruction based on students' feedback, *J. Comput. High. Educ.*, 35(1), pp:6–39.

[32] Qenani, E.; MacDougall, N. and Sexton, C. 2014.An empirical study of self-perceived employability: Improving the prospects for student employment success in an uncertain environment,*Act. Learn. High. Educ.*,15(3), pp:199–213.

[33] Stys, Y. and Brown, S. L. 2004. *A review of the emotional intelligence literature and implications for corrections (Vol. 340)*. Ottawa, ON, Canada: Research Branch, Correctional Service of Canada.,.

[34] Broo, D. G. ; Kaynak, O. and Sait, S. M. 2022. Rethinking engineering education at the age of industry 5.0,*J. Ind. Inf. Integr.*,25, pp:100311,.

[35] Perera, L. and Richardson, P. 2010. Students' use of online academic resources within a course web site and its relationship with their course performance: An exploratory study, *Account. Educ. an Int. J.*, 19(6), pp. 587–600.

[36] Porter, M. E. 1980. Industry structure and competitive strategy: Keys to profitability," *Financ. Anal. J.*, 36(4), pp:30–41.

[37] Hobfoll, S. E. and Freedy, J. 2017. Conservation of resources: A general stress theory applied to burnout," in *Professional burnout*, , pp:115–129.

[38] Kukreja, V. 2022. Hybrid fuzzy AHP–TOPSIS approach to prioritizing solutions for inverse reinforcement learning, *Complex Intell. Syst.*, Jul., doi: 10.1007/s40747-022-00807-5.

[39] A. Bhattacherjee, V. Kukreja, and A. Aggarwal, "Stakeholders' perspective towards employability: a hybrid fuzzy AHP-TOPSIS Approach," *Educ. Inf. Technol.*, 2023, doi: 10.1007/s10639-023-11858-7.

[40] Kukreja, V.;. Jain, A. K; Singh, A.; Kaushal, R. K. and Aggarwal, A. 2023.Analysing moderators and critical factors that affect early childhood education with the usage of touchscreen contrivances: A hybrid fuzzy AHP—fuzzy TOPSIS approach, *Educ. Inf. Technol.*,. 28(5,) pp:5621–5650, doi: 10.1007/s10639-022-11379-9.

[41] Chang, D. Y. 1996. Applications of the extent analysis method on fuzzy AHP, *Eur. J. Oper. Res.*, 95(3), pp:649–655, doi: 10.1016/0377-2217(95)00300-2.

[42] Aggarwal, A.; Kukreja, V. and Nobi, K. 2023 .Prioritising and testing the integrated behavioural model of organisational citizenship behaviour through fuzzy AHP & structural equation modelling,*Int J. Enterp. Netw.Manag.*,14(1–2),pp:1–24,doi:10.1504/IJENM.2023.1307 66.